A Scoping Review on the Application Scope of Digital Technology in Cognitive Impairment Screening

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Abstract

Objective This study aims to systematically review the application of digital technologies in early screening for cognitive impairment, summarize their progress, auxiliary effects, and limitations, and highlight the potential for optimization and further development in this field.

Methods Relevant studies were systematically retrieved from PubMed, Web of Science, Wanfang Data, CNKI, and VIP Database. The search period covered from the establishment of each database to October 10, 2025. The included studies were analyzed and summarized.

Results A total of 16 studies were included. The screening technologies involved attention mechanism-integrated Alzheimer's disease recognition models, machine learning, support vector machines, and others. The outcome indicators primarily included the accuracy, sensitivity, and specificity of digital technologies.

Conclusion Digital technologies have been applied to early screening for cognitive impairment and show preliminary promise, though their clinical effectiveness requires further validation. However, considerable heterogeneity exists in the evaluation tools for outcome indicators, and certain limitations remain in practical application. Future research should consider the specific characteristics of patients with suspected cognitive impairment and explore standardized procedures for the application of digital technologies in cognitive impairment screening.

Keywords: digital technology; artificial intelligence; cognitive impairment; screening; scoping review

Introduction

With the acceleration of global population aging, cognitive impairment has evolved from a purely medical issue into a major public health challenge, exerting multidimensional impacts on individual quality of life, family functioning, and healthcare systems. Cognitive impairment has become a significant public health concern faced by aging societies worldwide[1]. An estimated 55 million people globally are living with dementia, with prevalence projected to reach 139 million by 2050[2]. Older people face a markedly increased risk of dementia,

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and amnestic mild cognitive impairment (aMCI) carries a considerable risk of progression to Alzheimer's disease (AD); baseline MRI measures can help predict such conversion[3]. This condition places a substantial burden on healthcare systems.

For individual patients, the prolonged disease course and complex treatment regimens impose considerable physical and psychological distress, often accompanied by anxiety and depression. For families, long-term care demands not only consume significant human and material resources but may also lead to caregiver burnout and social isolation, severely affecting normal family functioning. For society, the status and influencing factors of cognitive function among the elderly have drawn increasing attention[4], and the rising costs of diagnosis, treatment, care, and related social services further strain the healthcare system.

Early identification and intervention are key to delaying disease progression and reducing societal burden. However, current clinical screening faces multiple bottlenecks. Traditional screening methods primarily rely on scale-based assessments, neuroimaging, and cerebrospinal fluid testing. Among these, scale-based assessments are susceptible to subjective bias, neuroimaging equipment is costly and difficult to widely implement, and cerebrospinal fluid testing, as an invasive procedure, has low patient acceptance. Although objective classification approaches such as support vector machines have been applied to the individual identification of amnestic mild cognitive impairment[5], they have not yet been widely adopted in routine clinical screening. These factors contribute to high missed diagnosis rates in the preclinical stages, causing many patients to miss the optimal window for early intervention. Furthermore, traditional screening tools are time-consuming, subjective, and unsuitable for primary care settings, with high false-negative rates due to the insidious nature of the disease[6]. Early screening is the optimal prevention and control strategy, yet traditional methods fall short, necessitating the exploration of digital technologies.

Therefore, there is an urgent need to develop accurate, convenient, and non-invasive early screening technologies in the field of cognitive impairment prevention and treatment. Various digital technologies can integrate multimodal data—including neuroimaging, electroencephalography (EEG), speech, and behavioral data—and achieve precise extraction and analysis of cognitive impairment-related features through algorithmic optimization, potentially improving screening accuracy and stability[7]. One study showed that daily interactions with humanoid robots could distinguish MCI patients from cognitively normal (CN) elderly individuals with 68.1% accuracy[8]. This digital technology-assisted identification may facilitate very early detection of the prodromal stage of AD and contribute to improving screening accuracy and stability. However, heterogeneity exists in the outcome indicators, and practical application faces limitations, requiring case-specific evaluation.

Accordingly, this study follows the scoping review framework to examine the intervention effects and outcome indicators of digital technology–based cognitive impairment screening, with the aim of understanding the current research status and providing a reference for future intervention studies to improve early screening accuracy. Compared with previous reviews, the present study focuses on technologies such as support vector machines (SVM) classifiers, machine learning, digital twins combined with non-invasive EEG recordings, and image preprocessing software in multimodal data processing and novel scenarios. The evaluation dimensions have also been expanded from accuracy alone to include sensitivity, specificity, jitter local value, and coefficient of variation of fundamental frequency.

Methods

Research questions

The specific review questions were as follows: (1) What digital technologies are available? (2) What are the screening contents, intervention effects, and outcome indicators of digital technology–based cognitive impairment screening? (3) How effective are digital technologies in cognitive impairment screening?

Inclusion and exclusion criteria

The inclusion criteria were: (1) older adults with normal cognition, subjective cognitive decline (SCD), MCI, AD, aMCI, or other related conditions; (2) studies

using digital technologies for cognitive impairment screening, identification, diagnostic assistance, or risk prediction; and (3) study designs including randomized controlled trials, quasi-experimental studies, and mixed-methods studies.

In this study, "digital technology" refers to technological tools that use computers, algorithms, or electronic hardware for cognitive impairment screening, identification, diagnostic assistance, or risk prediction. Based on the characteristics of the included literature, the digital technologies were classified into six categories: (1) neuroimaging analysis technologies (e.g., MRI-related technologies); (2) neuroelectrophysiological technologies (e.g., EEG analysis); (3) speech/language analysis technologies (e.g., language models, speech applications); (4) behavioral and passive monitoring technologies (e.g., in-home power monitoring, driving monitoring); (5) robot/mobile application interaction technologies (e.g., humanoid robots); and (6) multimodal fusion and artificial intelligence (AI) model technologies (e.g., digital twins, multimodal deep learning), and these six categories represent application-oriented groupings rather than mutually exclusive technological classifications.

Digital technology devices in this study include hardware such as EEG recorders, magnetic resonance imaging (MRI) scanners, and intelligent monitoring terminals, while applications, professional software, and algorithmic models are software and technical modules running on this hardware. All studies combining hardware and software for cognitive impairment screening were included.

The exclusion criteria were: (1) studies not involving digital technologies or lacking an experimental component; (2) literature not in Chinese or English; (3) full text unavailable; (4) duplicate publications; (5) studies providing only detection methods without a developed application; and (6) studies providing only algorithms without hardware carriers.

Search strategy

To comprehensively and systematically identify relevant literature on digital technologies for early cognitive impairment screening, this study developed a search strategy based on the PICOS framework, covering four dimensions: disease, study population, intervention technology, and study type. At the technical level, in addition to core concepts, supplementary search terms including deep learning, SVM, EEG, MRI, digital twins, humanoid robots, and speech analysis were added to cover the main technological directions identified in the included literature. Systematic searches were conducted in PubMed, Web of Science, Wanfang Data, CNKI, and VIP Database. The search period spanned from the establishment of each database to October 10, 2025, using a combination of MeSH terms and free-text terms. Manual tracing of references of all included literature and relevant reviews was performed to supplement any omitted literature and maximize coverage. All search terms were determined based on the PICOS framework and adapted to the syntax of each database. The search was conducted on October 10, 2025, and detailed search records for each database have been archived for reference.

Using PubMed as an example, the search query was:

#1 ("Digital Technology" [Title/Abstract] OR "Digital Tool*" [Title/Abstract] OR "Smartphone" [Title/Abstract] OR "Mobile Application*" [Title/Abstract] OR "Artificial Intelligence" [MeSH] OR "AI" [Title/Abstract] OR "Machine Learning" [MeSH] OR "Deep Learning" [Title/Abstract] OR "Support Vector Machine" [Title/Abstract] OR "SVM" [Title/Abstract] OR "Telemedicine" [MeSH] OR "Neuroimaging" [MeSH] OR "Magnetic Resonance Imaging" [MeSH] OR "Electroencephalography" [MeSH] OR "Digital Twin" [Title/Abstract] OR "Humanoid Robot*" [Title/Abstract])
#2 ("Cognitive Impairment" [MeSH] OR "Cognitive Disorder*" [Title/Abstract] OR "Mild Cognitive Impairment" [MeSH] OR "MCI" [Title/Abstract] OR "Alzheimer Disease" [MeSH] OR "Alzheimer*" [Title/Abstract] OR "Dementia" [MeSH] OR "Subjective Cognitive Decline" [Title/Abstract] OR "SCD" [Title/Abstract])
#3 ("Screening" [Title/Abstract] OR "Assessment" [Title/Abstract] OR "Early Diagnosis" [Title/Abstract] OR "Detection" [Title/Abstract] OR "Prediction" [Title/Abstract] OR "Classification" [Title/Abstract])
#4 Search (#1 AND #2 AND #3)

For Chinese databases, using CNKI as an example, the search query was:

(SU = '数字技术' OR SU = '人工智能' OR SU = '机器学习' OR SU = '深度学习' OR SU = '支持向量机' OR SU = '磁共振成像' OR SU = '脑电' OR SU = '数字孪生' OR SU = '仿人机器人' OR SU = '远程医疗') AND (SU = '认知障碍' OR SU = '阿尔茨海默病' OR SU = '痴呆' OR SU = '轻度认知障碍' OR SU = 'MCI' OR SU = '主观认知下降') AND (SU = '筛查' OR SU = '评估' OR SU = '早期诊断' OR SU = '预测')

Literature screening and data extraction

Literature screening

The retrieved literature was imported into EndNote software. After removing duplicates, two researchers independently performed initial screening based on the inclusion and exclusion criteria, followed by full-text screening. In cases of disagreement during the screening process, the two researchers consulted with a third researcher to reach a consensus and determine the final included literature.

Data extraction

Data extraction from the included literature was independently conducted by two researchers who had received systematic evidence-based nursing training. In cases of disagreement or uncertainty during the extraction process, they consulted with a third researcher. The extracted data items included: authors, country, publication year, digital technology devices, screening frequency/duration, sample size (experimental group/control group), and outcome indicators.

Quality assessment of included literature

This study is a scoping review and follows the PRISMA-ScR guidelines. Its primary purpose is to systematically map the range of digital technologies used in cognitive impairment screening, their technical types, and outcome indicators, rather than to conduct methodological quality assessment or risk of bias evaluation of the included studies. Therefore, this study did not perform quality assessment of the included literature. However, through dual independent screening, third-researcher adjudication, standardized data extraction forms, and cross-checking procedures, the accuracy and completeness of the extracted information were ensured.

Results

Literature search results and basic characteristics of included literature

A total of 1,412 records were identified through database searching. After removing duplicates, 1,397 records remained. Following initial screening by reading titles and abstracts, 1,026 records were excluded (550 due to irrelevant topic, 467 due to ineligible study population or intervention), leaving 371 records. After full-text screening, an additional 355 records were excluded (85 due to irrelevant content, 51 as conference abstracts, and 219 due to unavailable full text), resulting in 16 studies finally included. The literature screening process is shown in Figure 1, and the basic characteristics of the included literature are presented in Table 1. The preceding text has categorized the digital technologies, algorithmic models, image processing tools, and mobile applications used in early cognitive impairment screening. To clearly present the overall landscape of existing research, Table 1 summarizes the basic characteristics of all included studies and specifies the digital screening technologies and application carriers used in each, mapping each study's basic information to its technological approach.

Types of digital technologies for cognitive impairment screening

All technologies used in the included studies were classified as digital technologies. According to the six-category framework described above, the distribution was as follows: neuroimaging analysis (6 studies)[9–14], neuroelectrophysiology (1 study)[20], speech/language analysis (2 studies)[17,18], behavioral and passive monitoring (2 studies)[21,23], robot/mobile application interaction (2 studies)[16,19], and multimodal fusion with AI models (3 studies)[15,22,24]. Specific technological approaches included support vector machines, SVM classifiers, machine learning, digital twins combined with non-invasive EEG recording, and image preprocessing software. Other approaches comprised multiview-slice attention with 3D-CNN for brain structure analysis, artificial intelligence, the Novoic mobile application, attention mechanism-integrated AD recognition models, the dVAE-BERT language model, automatic resting-state

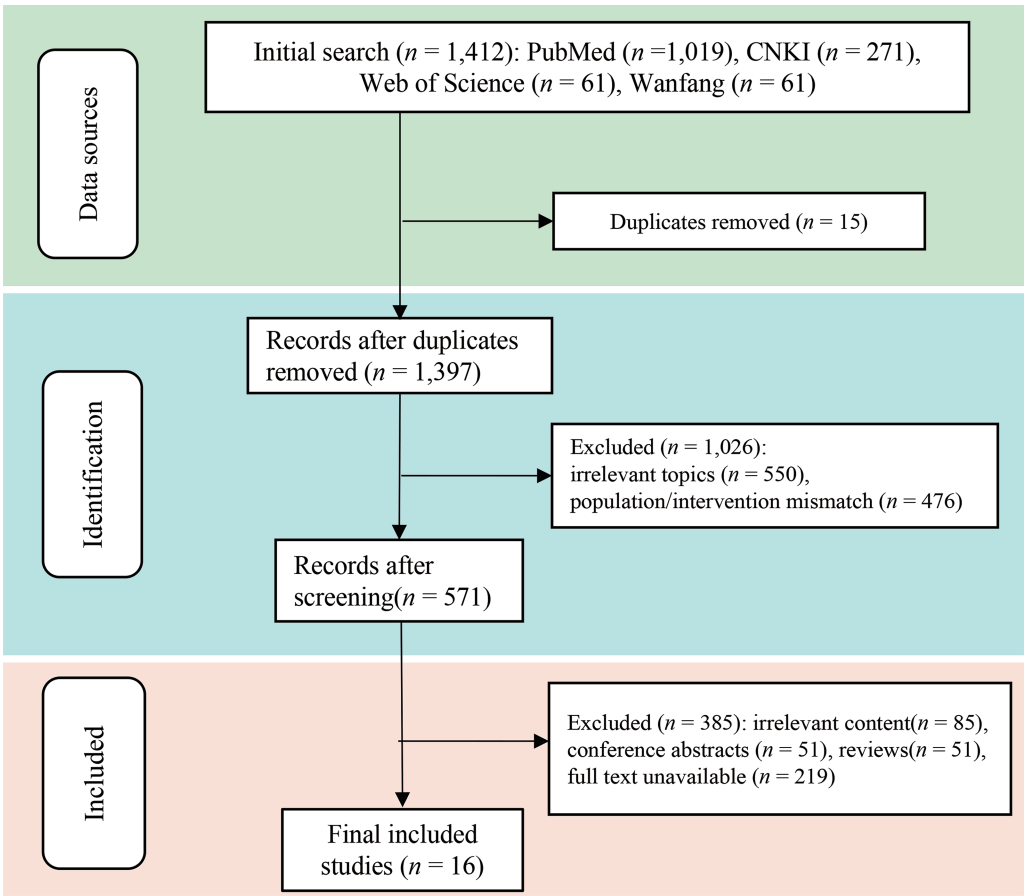


Figure 1: Literature screening process.

EEG detection based on feature fusion, thin-slice MRI combined with AI-based brain segmentation software, multimodal deep learning integrating MRI and single nucleotide polymorphism data, non-invasive in-home power monitoring, and explainable machine learning models.

Types and content of digital technologies in cognitive impairment screening

The types and content of digital technologies in cognitive impairment screening were diverse. Most studies had relatively short screening durations. In terms of multimodal data fusion, some studies integrated neuroimaging (e.g., MRI, EEG), speech, and behavioral data to assist in cognitive impairment screening. In machine learning applications, semi-supervised learning was combined with ensemble learning to fine-tune models using unlabeled data, while methods such as Shapley Additive Explanations (SHAP) were employed to enhance model interpretability, identifying key features such as education level and decline in daily living function that influence cognitive impairment prediction. In addition, some studies developed non-invasive and real-time monitoring technologies, such as in-vehicle multimodal sensor systems and humanoid robot dialogue systems, which can be integrated into portable devices, offering new pathways for real-time non-invasive screening. Some studies even combined digital twin models to dynamically simulate pathological mechanisms, reducing reliance on invasive testing.

Experimental procedures and outcome indicators

Experimental procedures

The experimental approaches in the included studies were diverse. Six studies involved structural imaging analysis, primarily using MRI to quantify structural

Table 1: Basic characteristics of included literature ($n = 16$).

Included literature	Country	Year	Digital technology device	Screening frequency/ duration	Sample size (experimental/ control)	Outcome indicators
Zeng and Gao[9]	China	2021	AD recognition model integrating attention mechanism	5 training sessions per binary classification	NR	Number of brain regions
Wang et al.[10]	China	2024	Thin-slice MRI + AI brain segmentation software	2 min 22 s	148/50	Brain region volumes and percentages
Chen et al.[11]	China	2022	Multi-view slice attention + 3D-CNN	NR	1,038/413	Accuracy, sensitivity, specificity, AUC, F1
Zhang et al.[12]	China	2014	Support vector machine, SVM classifier	NR	51/68	Whole-brain gray matter volume atlas
Davatzikos et al.[13]	USA	2008	Image preprocessing + SVM	15–20 min/session	15/15	Specific brain regions/parameters
Li et al.[15]	China	2025	MRI + SNP multimodal deep learning	NR	974/567	Accuracy, sensitivity, specificity, F1
Amato et al.[15]	Italy	2025	Digital twin + non-invasive EEG	NR	105/19	Accuracy, AUC, precision, sensitivity/ specificity
Formica et al.[16]	Italy	2025	Humanoid robot, AI	NR	50/50	Accuracy, sensitivity, specificity
Chen et al.[17]	China	2024	dVAE-BERT language model	Approximately 5.05 hours total	87/71	Model accuracy, precision, recall
Fristed et al.[18]	UK	2022	Novoic mobile app	7–8 consecutive days	62/71	Aβ-positive detection, ASRT prediction vs. automatic transcription
Yoshii et al.[19]	Japan	2023	Humanoid robot	NR	47/47	Reaction time, voiced/ silent/filler duration and ratio
Duan et al.[20]	China	2022	Automatic resting-state EEG detection based on feature fusion	5 min	22/57	Brain network types, power brain network performance
Al-Hindawi et al.[21]	USA	2025	Machine learning	Varies with driving speed	8/13	Accuracy, sensitivity, specificity, PPV, NPV, mean ± SD per fold
Yue et al.[22]	China	2023	Explainable machine learning model	NR	654/2,004	Accuracy, sensitivity, specificity, geometric mean, AUC
Nakaoku et al.[23]	Japan	2021	Non-invasive in-home power monitoring	>1 year follow-up	23/55	Accuracy, sensitivity, specificity
Umeda-Kameyama et al.[24]	Japan	2021	AI	NR	121/117	Accuracy, loss, stability

Note: NR indicates that the data were not reported in the original study. Abbreviations: AD, Alzheimer's disease; dVAE-BERT; discrete Variational Autoencoder-Bidirectional Encoder Representations from Transformers; EEG, electroencephalography; MRI, magnetic resonance imaging; AI, artificial intelligence; SVM, support vector machine; PPV, positive predictive value; NPV, negative predictive value; AUC, area under the curve; 3D-CNN, three-dimensional convolutional neural network; SNP, single nucleotide polymorphism.

changes in brain regions. Among these, three focused on brain region volume and morphometry to differentiate mild cognitive impairment (MCI) from AD[9–11]; two examined regional density and textural features to compare structural differences between cognitively impaired patients and healthy controls[12,13]; and one

conducted multimodal imaging fusion analysis to improve the specificity of early AD screening[14]. Two studies applied neuroelectrophysiological analysis to EEG data: one used an automatic resting-state EEG detection approach based on feature fusion[20], and one integrated a digital twin model with non-invasive EEG recordings[15]. Two studies analyzed speech recordings from picture description tasks: one used acoustic feature analysis[18], and one employed the dVAE-BERT language model for semantic and linguistic analysis[17]. Four studies involved human-robot interaction and behavioral monitoring: two used humanoid robot-based assessments[15,19], one analyzed in-vehicle driving behavior[21], and one monitored in-home electrical power use[23]. Two studies applied artificial intelligence to screening based on clinical and imaging data, including an explainable machine learning model using lifestyle and clinical characteristics[22] and facial image analysis[24].

One study reported that the model required relatively low hardware resources yet maintained high performance[9]. Twelve studies found that the recognition models showed improved accuracy and stability[10–15,18,20–24]. Two studies indicated that digital technology application could reduce misdiagnosis rates[16,19]. One study noted that personalized intervention plans could be developed[15]. One study found that prior knowledge bias could be reduced[17]. One study reported that digital technology could serve a supportive role[18]. One study demonstrated that adjustments could be made for individual differences[23]. One study found that robustness and generalizability during digital technology–based detection could be enhanced[22].

Outcome indicators

One study reported that after applying the relevant digital technology, the accuracy for detecting MCI reached 89.2%, and for AD reached 99.2%, with sensitivity of 87.7% and 99.7%, respectively. Specificity, G-mean, AUC, and other metrics also showed notable improvements[9]. Another study reported an accuracy of 66%, sensitivity of 70.2%, and specificity of 66% for cognitive impairment screening, with significant differences in jitter local value ($P < 0.001$, $r = 0.10$) and coefficient of variation of fundamental frequency ($P < 0.001$)[17], suggesting that digital technology may have auxiliary value in cognitive impairment screening. One study measured and evaluated accuracy, sensitivity, specificity, AUC, and optimal thresholds across different age groups, finding a declining trend with increasing age[20]. Another study compared two digital technologies and found that after technological improvement, the accuracy of electrical monitoring data increased from 76% to 82%, sensitivity from 30% to 48%, and positive and negative predictive values from 70% and 86% to 85% and 90%, respectively[10]. The comparisons of accuracy, sensitivity, and specificity before and after showed statistically significant differences, indicating that digital technology may play an auxiliary role in cognitive impairment screening. In addition, the study found that the indicators of digital technology in cognitive impairment screening showed a declining trend with increasing age, suggesting that age should be considered as a factor in practical applications, and screening protocols may be adjusted accordingly for different age groups.

Cross-study comparison of key characteristics

To systematically assess heterogeneity across studies, key elements of the included literature were compared horizontally (see Table 2). The main patterns identified were as follows:

In terms of target populations and disease stages, digital technologies performed best in distinguishing AD from CN (accuracy generally > 88%), with lower performance in distinguishing MCI from CN (accuracy 70%–85%) and in predicting pMCI vs. sMCI (accuracy 65%–80%), suggesting that further improvement is needed for detecting subtle early cognitive changes.

Regarding sample size and validation methods, the median sample size was approximately 100 cases, with only two studies exceeding 500 cases[11,14]. Ten studies used cross-validation[9,11–14,17–20,22], but only two[11,14] performed cross-database external validation, indicating insufficient evidence for model generalizability.

In terms of data modalities and performance, single-modality studies dominated (11/16), while only five studies[14,15,17,18,21] used multimodal approaches. Multimodal studies generally outperformed single-modality studies, but their smaller sample sizes suggest that conclusions

Table 2: Cross-study comparison of key characteristics.

Included literature	Target population	Data modality	Model type	Validation method	Key performance metrics
Zeng and Gao[9]	AD/HC/MCI	MRI	Attention mechanism + ensemble learning	5-fold cross-validation	random forest (Acc) 88%
Wang et al.[10]	AD/VD	Thin-slice MRI + AI segmentation	AI segmentation software	NR	AUC 0.87
Chen et al.[11]	AD/CN/pMCI/sMCI	MRI	3D-CNN + attention	Cross-database validation	Acc 91.1%, AUC 0.95
Zhang et al.[12]	aMCI	MRI	SVM	Leave-one-out cross-validation	Acc 83.2%, sensitivity (Sen) 76.5%, specificity (Spe) 88.2%, AUC 0.84
Davatzikos et al.[13]	MCI	MRI	SVM + image preprocessing	Leave-one-out cross-validation	Acc 90%
Li et al.[14]	AD/NC/pMCI/sMCI	MRI + SNP	Multimodal deep learning	Independent test set	Acc 93.0%, Sen 91.1%, Spe 93.8%
Amato et al.[15]	SCD	EEG + digital twin	Digital twin model	Nested cross-validation	Acc 88%, AUC 0.80
Formica et al.[16]	MCI	Humanoid robot	Human-robot interaction + AI	NR	Acc 86%, Sen 72%, Spe 91%
Chen et al.[17]	AD	Speech	dVAE-BERT	Independent test set	Acc 70.4%, Spe 66%
Fristed et al.[18]	MCI/AD	Speech + smartphone	Novoic App + AI	Leave-pair-out cross-validation	AUC 0.85
Yoshii et al.[19]	MCI	Humanoid robot conversation	SVM	5-fold cross-validation	Acc 68.1%, Sen 70.2%, Spe 66%
Duan et al.[20]	MCI	Resting-state EEG	CNN + feature fusion	5-fold cross-validation	Acc 92.7%, Sen 90.0%, Spe 95.2%
Al-Hindawi et al.[21]	MCI	Driving behavior data	QDA/KNN/RF	4-fold cross-validation	Acc 72%, Sen 38%, Spe 92%
Yue et al.[22]	AD/MCI	Lifestyle + clinical data	Explainable ensemble learning	10-fold cross-validation	Acc 99.2%, Sen 99.7%, Spe 98.7%, AUC 1.0
Nakaoku et al.[23]	MCI	In-home power monitoring	Generalized linear mixed model	NR	Acc 82%, Sen 48%, Spe 96%
Umeda-Kameyama et al.[24]	AD	Facial images	Xception deep learning	10-fold cross-validation	Acc 92.6%, Sen 87.3%, Spe 94.6%, AUC 0.97

Note: NR indicates that the information was not reported in the original study. Abbreviations: AD, Alzheimer's disease; HC, healthy control; MCI, mild cognitive impairment; MRI, magnetic resonance imaging; VD, vascular dementia; AI, artificial intelligence; AUC, area under the curve; CN, cognitively normal; pMCI, progressive mild cognitive impairment; sMCI, stable mild cognitive impairment; 3D-CNN, three-dimensional convolutional neural network; aMCI, amnestic mild cognitive impairment; SVM, support vector machine; NC, normal control; SNP, single nucleotide polymorphism; SCD, subjective cognitive decline; EEG, electroencephalography; dVAE-BERT; discrete Variational Autoencoder-Bidirectional Encoder Representations from Transformers; CNN, convolutional neural network; QDA, quadratic discriminant analysis; KNN, K-nearest neighbors; RF, random forest.

require further verification.

Regarding key performance metrics, accuracy ranged from 66% to 99.2%, sensitivity from 38% to 99.7%, specificity from 66% to 98.7%, and AUC from 0.72 to 1.0. The overall trend indicated that performance was best for AD vs. CN classification, followed by MCI vs. HC, and lowest for pMCI vs. sMCI prediction, suggesting

that digital technologies perform better in distinguishing more clinically distinct stages.

Discussion

Digital technology–based cognitive impairment screening: diverse types with promising accuracy and stability

The findings of this review indicate that various types of digital technologies have shown promise in early cognitive impairment screening. In neuroimaging analysis, one study reported that potential AD risk at the MCI stage could be identified, with brain region abnormalities detected 3–5 years earlier than conventional MRI visual assessment[13]. In multimodal fusion and AI models, one model assessed MCI risk through lifestyle characteristics (e.g., education level) before clinical symptom onset[22]. In robot interaction and behavioral monitoring, humanoid robots can be deployed outside specialized medical settings and are less costly than MRI examinations[16,19], making them suitable for large-scale community screening. These findings suggest that researchers may select appropriate digital technology categories based on different screening scenarios (community-based large-scale screening vs. clinical precision diagnosis).

Heterogeneity in outcome indicators across digital technology–based screening

This heterogeneity was evident across core dimensions of model performance. The MRI model integrating a direct-mapping attention mechanism achieved an accuracy of 0.88 ± 0.03 for AD vs. HC classification[9]. The QDA model in LiveDrive AI achieved an accuracy of (72 ± 10)% and a sensitivity of (38 ± 48)% (mean ± SD across cross-validation folds)[21], while the speech-based dVAE-BERT model achieved an accuracy of 70.42% on the ADReSSo dataset[17]. For MCI identification, the power brain network feature-fusion model reported a sensitivity of 90.0% for the selected feature configuration[18]. Wang et al. reported an AUC of 0.87 for medial temporal lobe volume percentage in identifying dementia, rather than specifically AD[10]. Yue et al. reported an AUC of 1.0 for AD versus normal-control classification using an explainable ensemble model[22]. These estimates were obtained in different populations, classification tasks, and validation settings and should not be interpreted as direct comparisons of the technologies. Differences in data modalities, feature selection, model architecture, and evaluation design may contribute to the observed heterogeneity. Further studies using comparable populations and independent validation are needed to establish screening performance.

Limitations of digital technology–based cognitive impairment screening in practice

Several limitations affect the practical application of these technologies. Some studies used small, single-source samples. The power brain network model was evaluated using 41 participants (20 with mild cognitive decline and 21 healthy controls) selected from a hospital dataset in Shanghai[20]. The SVM study included 51 aMCI patients and 68 healthy controls[12], and the LiveDrive AI pilot study included 21 participants (13 healthy controls and 8 with MCI)[21]. Such samples may not adequately capture variation across regions, ethnicities, and disease subtypes, limiting generalizability. Larger and more diverse samples are needed to assess whether these findings extend to broader screening populations.

In addition, the diagnostic performance estimates (e.g., accuracy, sensitivity, specificity, AUC) reported across the included studies should be interpreted with caution. Although many studies reported promising metrics, the risk of overfitting cannot be ignored, as most models were developed and evaluated on relatively small, single-source datasets without external validation. Moreover, substantial variation exists in validation approaches, including cross-validation methods and the use of independent test sets. These methodological differences may contribute to the heterogeneity in reported performance and limit the direct comparability of findings across studies.

Future large-sample trials and longitudinal studies are needed to validate the effectiveness, accuracy, and extent of digital technology–based cognitive impairment screening.

Impact of study time span and technological evolution

The publication years of the included studies spanned a considerable period (2008–2025), during which digital

technologies underwent significant evolution. Early studies (e.g., Davatzikos et al.[13]) primarily used traditional machine learning methods (e.g., support vector machines) with manually extracted features from MRI images for classification. In contrast, recent studies have widely adopted emerging technologies such as deep learning (e.g., CNN, Transformer), multimodal fusion, and digital twins. This technological evolution reflects the rapid development of the field but also complicates direct comparisons of findings across different time periods. This review did not simply compare technologies from different eras directly, but instead extracted the core performance indicators (accuracy, sensitivity, specificity) from each study and traced the development of each technology category within a classification framework, aiming to extract valuable insights from heterogeneity. Future research should further examine the incremental value of technological iteration for screening effectiveness.

Conclusion

This review included 16 studies and conducted a scoping review of the literature on digital technology–based cognitive impairment screening. The results indicate that digital technologies are diverse in type and show preliminary promise in cognitive impairment screening, suggesting potential to improve screening accuracy and stability; however, these findings are based on a limited evidence base. However, considerable heterogeneity existed across the included studies in terms of diagnostic criteria, study populations, and sample sizes, and most studies lacked external validation. Therefore, the above conclusions should be interpreted with caution.

Future research may focus on the following directions: (1) establishing standardized procedures adapted to national contexts, developing operational guidelines for digital technology screening that consider the characteristics of the Chinese elderly population (e.g., high proportion with low education levels, uneven distribution of community medical resources), and clarifying the applicable scenarios, sample inclusion criteria, and core indicators for different technologies; (2) expanding sample sizes and validation dimensions through multicenter studies with over 1,000 cases, while incorporating longitudinal data to verify the predictive value of digital technologies for cognitive impairment progression, with particular attention to early stages such as SCD and aMCI; (3) promoting technology integration and optimization by combining the advantages of multimodal data; (4) addressing the adaptability of special populations by optimizing technical operations for older adults, individuals with disabilities, and those with low education levels to improve screening accessibility; and (5) improving the evaluation system by supplementing accuracy with indicators such as screening time, cost-effectiveness, and patient acceptance, providing a comprehensive basis for the clinical translation of digital technologies.

Author contributions

Ruiqi Zhao: conceptualization, writing-original draft, data curation; Yuying Wu: methodology, formal analysis, visualization; Shihua Cao: conceptualization, supervision, writing-review & editing, project administration; Haowen An: resources, validation, writing-review & editing.

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Data availability statement

No datasets were generated or analyzed for this work.

Ethics statement

Not applicable.

AI statement

The authors used GPT-4 as a language-editing tool to improve grammar, clarity, and readability. The AI tool was not used for data analysis, data generation, image

processing, or scientific content creation. All outputs were carefully reviewed and verified by the authors, who take full responsibility for the final content.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Zheng HG. Precision prevention of cognitive impairment: challenges and opportunities. *Chinese Journal of Health Management*. 2025;19(8):581-584.
2. World Health Organization. *Global Status Report on the Public Health Response to Dementia 2021*. Geneva: World Health Organization; 2021.
3. Risacher SL, Saykin AJ, West JD, et al. Baseline MRI predictors of conversion from MCI to probable AD in the ADNI cohort. *Curr Alzheimer Res*. 2009;6(4):347-361.
4. Huang JH, Fu QH, Feng TY, Zhang Q. Analysis of the status and influencing factors of cognitive function in the elderly. *Chinese Journal of Convalescent Medicine*. 2022;31(8):793-796.
5. Han Y. Individual identification research of amnestic mild cognitive impairment based on support vector machine. In: Proceedings of the 17th National Neurology Academic Conference of Chinese Medical Association; 2014; Xiamen, China. Chinese Medical Association; 2014:1065-1065.
6. Chen Y, Wang L. Limitations of cognitive screening scales for mild cognitive impairment and emerging auxiliary detection strategies. *J Clin Neurosci*. 2024;126:109-115.
7. Bonvino A, Cornacchia E, Scaramuzzi GF, et al. Digital Tools for Mild Cognitive Impairment: A Systematic Review and Meta-analysis of Diagnostic Accuracy and Methodological Challenges. *Neuropsychology Rev*. 2025.
8. Kobayashi M, Yamada Y, Nemoto M, et al. Screening of mild cognitive impairment through conversations with humanoid robots: exploratory pilot study. *JMIR Form Res*. 2023;7:e42792.
9. Zeng A, Gao Z. Alzheimer's disease recognition model incorporating attention mechanism. *Journal of Biomedical Engineering Research*. 2021;40(3):233-240.
10. Wang HC, Wang QF, Luo CG. Study of magnetic resonance thin-layer scanning combined with artificial intelligence brain segmental software for diagnosis and typing of senile dementia. *Clinical Education of General Practice*. 2024;22(11):970-973.
11. Chen L, Qiao H, Zhu F. Alzheimer's disease diagnosis with brain structural MRI using multiview-slice attention and 3D convolution neural network. *Front Aging Neurosci*. 2022;14:871706.
12. Zhang ZM, Cui ZX, Guo YQ, et al. Individual identification research of amnestic mild cognitive impairment based on support vector machine. *J Med Postgrad*. 2014;27(8):814-819.
13. Davatzikos C, Fan Y, Wu X, Shen D, Resnick SM. Detection of prodromal Alzheimer's disease via pattern classification of magnetic resonance imaging. *Neurobiology of Aging*. 2008;29(4):514-523.
14. Li Y, Niu D, Qi K, Liang D, Long X. An imaging and genetic-based deep learning network for Alzheimer's disease diagnosis. *Front Aging Neurosci*. 2025;17:1532470.
15. Amato LG, Lassi M, Vergani AA, et al. Digital twins and non-invasive recordings enable early diagnosis of Alzheimer's disease. *Alz Res Therapy*. 2025;17(1):125.
16. Formica C, Giambò FM, Latella D, et al. Humanoid robots for psychological assessment in mild cognitive impairment: from evaluation to the future of AI-driven data prediction systems. *Front Psychol*. 2025;16:1579626.
17. Chen XC, Pu Y, Zhang WQ. Detection of Alzheimer's disease based on dVAE-BERT model. *Acta Electronica Sinica*. 2024;52(9):2971-2978.
18. Fristed E, Skirrow C, Meszaros M, et al. A remote speech-based AI system to screen for early Alzheimer's disease via smartphones. *Alzheimers Dement (Amst)*. 2022;14(1):e12366.
19. Yoshii K, Kimura D, Kosug A, et al. Screening of mild cognitive impairment through conversations with humanoid robots: exploratory pilot study. *JMIR Form Res*. 2023;7:e42792.
20. Duan ZJ, Zhao BL, Li CB, Guo W. Automatic detection technology of resting state EEG data for mild cognitive decline based on convolutional neural network. *Application Research of Computers*. 2022;39(4):1137-1142,1167.
21. Al-Hindawi F, Serhan P, Geda YE, Tsow F, Wu T, Forzani E. LiveDrive AI: a pilot study of a machine learning-powered diagnostic system for real-time, non-invasive detection of mild cognitive impairment. *Bioengineering (Basel)*. 2025;12(1):86.
22. Yue L, Chen W, Liu S, Chen S, Xiao S. An explainable machine learning based prediction model for Alzheimer's disease in China longitudinal aging study. *Front Aging Neurosci*. 2023;15:1267020.
23. Nakaoku Y, Ogata S, Murata S, et al. AI-assisted in-house power monitoring for the detection of cognitive impairment in older adults. *Sensors (Basel)*. 2021;21(18):6249.
24. Umeda-Kameyama Y, Kameyama M, Tanaka T, et al. Screening of Alzheimer's disease by facial complexion using artificial intelligence. *Aging (Albany NY)*. 2021;13(2):1765-1772.